autogluon_each_location

October 7, 2023

[69]:
```python
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X



def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")

    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = 3
    X_test["sample_weight"] = 3

    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600
```

```python
    X_train_estimated["estimated_diff_hours"] = X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])

    # fill missng sample_weight with 3
    #X_train["sample_weight"] = X_train["sample_weight"].fillna(0)


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True, right_index=True)

    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")
```

```python
    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[66]:
```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
# weekday or is_weekend
X_train["is_weekend"] = X_train["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_train.drop(columns=["weekday"], inplace=True)
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday

# weekday or is_weekend
X_test["is_weekend"] = X_test["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_test.drop(columns=["weekday"], inplace=True)
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year



to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

[67]:
```
import autogluon.eda.auto as auto
auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",␣
↪sample=None)
```

train_data dataset summary

```
                            count  unique top   freq           mean  \
absolute_humidity_2m:gm3    92951     165                  6.017608
air_density_2m:kgm3         92951     293                  1.255435
ceiling_height_agl:m        72276   40993               2802.587891
clear_sky_energy_1h:J       92951   48602              515154.03125
clear_sky_rad:W             92951    7815                143.101395
cloud_base_agl:m            84404   34862               1692.934692
```

dew_or_rime:idx	92951	3			0.007025
dew_point_2m:K	92951	436			275.237823
diffuse_rad:W	92951	2870			39.495811
diffuse_rad_1h:J	92951	48553			142180.03125
direct_rad:W	92951	5296			50.205017
direct_rad_1h:J	92951	41885			180740.1875
effective_cloud_cover:p	92951	1001			67.013527
elevation:m	92951	3			11.401738
estimated_diff_hours	92951	26			3.143516
fresh_snow_12h:cm	92951	125			0.116175
fresh_snow_1h:cm	92951	39			0.00963
fresh_snow_24h:cm	92951	161			0.229894
fresh_snow_3h:cm	92951	70			0.029001
fresh_snow_6h:cm	92951	96			0.058069
hour	92951	24			11.501339
is_day:idx	92951	2			0.483341
is_in_shadow:idx	92951	2			0.565384
is_weekend	92951	2			0.286775
location	92951	3	A	34061	
month	92951	12			6.294521
msl_pressure:hPa	92951	874			1009.502563
precip_5min:mm	92951	64			0.005674
precip_type_5min:idx	92951	7			0.083259
pressure_100m:hPa	92951	888			995.81897
pressure_50m:hPa	92951	897			1001.949646
prob_rime:p	92951	700			0.756834
rain_water:kgm2	92951	11			0.009677
relative_humidity_1000hPa:p	92951	788			73.669556
sample_weight	92951	2			1.23507
sfc_pressure:hPa	92951	902			1008.107849
snow_depth:cm	92951	165			0.193203
snow_melt_10min:mm	92951	19			0.000275
snow_water:kgm2	92951	42			0.090324
sun_azimuth:d	92951	69692			182.386337
sun_elevation:d	92951	49376			-1.207574
super_cooled_liquid_water:kgm2	92951	15			0.056944
t_1000hPa:K	92951	447			279.431091
total_cloud_cover:p	92951	1001			73.604256
visibility:m	92951	85686			33027.933594
weekday	92951	7			3.002184
wind_speed_10m:ms	92951	119			3.037911
wind_speed_u_10m:ms	92951	188			0.662565
wind_speed_v_10m:ms	92951	167			0.6824
wind_speed_w_1000hPa:ms	92951	3			-0.000016
y	92951	12423			287.232321
year	92951	5			2020.693193

std min 25% \

absolute_humidity_2m:gm3	2.714546	0.5	4.0
air_density_2m:kgm3	0.036608	1.139	1.23
ceiling_height_agl:m	2521.408447	27.799999	1037.099976
clear_sky_energy_1h:J	820525.5	0.0	0.0
clear_sky_rad:W	228.507324	0.0	0.0
cloud_base_agl:m	1790.963745	27.4	572.200012
dew_or_rime:idx	0.246032	-1.0	0.0
dew_point_2m:K	6.83461	247.300003	270.700012
diffuse_rad:W	60.647518	0.0	0.0
diffuse_rad_1h:J	215907.21875	0.0	0.0
direct_rad:W	112.946068	0.0	0.0
direct_rad_1h:J	401735.03125	0.0	0.0
effective_cloud_cover:p	35.044811	0.0	41.299999
elevation:m	7.877236	6.0	6.0
estimated_diff_hours	8.935328	0.0	0.0
fresh_snow_12h:cm	0.780374	0.0	0.0
fresh_snow_1h:cm	0.112621	0.0	0.0
fresh_snow_24h:cm	1.218249	0.0	0.0
fresh_snow_3h:cm	0.28067	0.0	0.0
fresh_snow_6h:cm	0.481389	0.0	0.0
hour	6.920153	0.0	6.0
is_day:idx	0.499725	0.0	0.0
is_in_shadow:idx	0.495709	0.0	0.0
is_weekend	0.452258	0.0	0.0
location			
month	3.585604	1.0	3.0
msl_pressure:hPa	13.089046	944.299988	1001.400024
precip_5min:mm	0.033511	0.0	0.0
precip_type_5min:idx	0.384904	0.0	0.0
pressure_100m:hPa	13.008334	929.799988	987.799988
pressure_50m:hPa	13.067102	935.599976	993.900024
prob_rime:p	5.434649	0.0	0.0
rain_water:kgm2	0.042968	0.0	0.0
relative_humidity_1000hPa:p	14.328553	19.5	64.199997
sample_weight	0.644117	1.0	1.0
sfc_pressure:hPa	13.128181	941.400024	1000.0
snow_depth:cm	1.254293	0.0	0.0
snow_melt_10min:mm	0.004312	-0.0	-0.0
snow_water:kgm2	0.250991	0.0	0.0
sun_azimuth:d	102.913605	0.008	92.794003
sun_elevation:d	24.010485	-49.979	-18.511
super_cooled_liquid_water:kgm2	0.111482	0.0	0.0
t_1000hPa:K	6.520342	257.899994	274.899994
total_cloud_cover:p	34.993042	0.0	51.700001
visibility:m	18319.150391	130.600006	15798.950195
weekday	2.001722	0.0	1.0
wind_speed_10m:ms	1.778505	0.0	1.7
wind_speed_u_10m:ms	2.808995	-7.3	-1.4

wind_speed_v_10m:ms	1.896996	-9.3	-0.6
wind_speed_w_1000hPa:ms	0.006502	-0.1	0.0
y	766.670114	-0.0	0.0
year	1.18587	2019.0	2020.0

	50%	75%	max \
absolute_humidity_2m:gm3	5.4	7.8	17.5
air_density_2m:kgm3	1.255	1.279	1.441
ceiling_height_agl:m	1803.25	3814.824951	12431.299805
clear_sky_energy_1h:J	4544.899902	778247.25	3006697.25
clear_sky_rad:W	0.0	220.949997	835.299988
cloud_base_agl:m	1128.550049	2016.699951	11688.900391
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	275.0	280.5	293.799988
diffuse_rad:W	0.0	66.0	340.100006
diffuse_rad_1h:J	9951.700195	236502.75	1182265.375
direct_rad:W	0.0	29.0	684.299988
direct_rad_1h:J	0.0	113366.25	2445897.0
effective_cloud_cover:p	80.800003	99.300003	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	0.0	0.0	39.0
fresh_snow_12h:cm	0.0	0.0	37.400002
fresh_snow_1h:cm	0.0	0.0	7.1
fresh_snow_24h:cm	0.0	0.0	37.400002
fresh_snow_3h:cm	0.0	0.0	20.6
fresh_snow_6h:cm	0.0	0.0	34.0
hour	12.0	17.0	23.0
is_day:idx	0.0	1.0	1.0
is_in_shadow:idx	1.0	1.0	1.0
is_weekend	0.0	1.0	1.0
location			
month	6.0	10.0	12.0
msl_pressure:hPa	1010.299988	1018.599976	1044.099976
precip_5min:mm	0.0	0.0	1.38
precip_type_5min:idx	0.0	0.0	6.0
pressure_100m:hPa	996.799988	1004.900024	1030.900024
pressure_50m:hPa	1002.900024	1011.099976	1037.300049
prob_rime:p	0.0	0.0	97.199997
rain_water:kgm2	0.0	0.0	1.4
relative_humidity_1000hPa:p	76.0	85.099998	100.0
sample_weight	1.0	1.0	3.0
sfc_pressure:hPa	1009.0	1017.200012	1043.800049
snow_depth:cm	0.0	0.0	18.299999
snow_melt_10min:mm	0.0	-0.0	0.18
snow_water:kgm2	0.0	0.1	6.9
sun_azimuth:d	179.526001	271.503494	359.997009
sun_elevation:d	-0.99	15.538	49.917999
super_cooled_liquid_water:kgm2	0.0	0.1	1.4

```
t_1000hPa:K                    278.700012   283.899994   303.299988
total_cloud_cover:p             94.800003        100.0        100.0
visibility:m                 37350.300781 48679.550781 76737.796875
weekday                               3.0          5.0          6.0
wind_speed_10m:ms                     2.7          4.1         15.2
wind_speed_u_10m:ms                   0.3          2.5         12.2
wind_speed_v_10m:ms                   0.7          1.9          9.0
wind_speed_w_1000hPa:ms               0.0          0.0          0.1
y                                     0.0     173.3625      5733.42
year                               2021.0       2022.0       2023.0

                                dtypes missing_count missing_ratio raw_type  \
absolute_humidity_2m:gm3       float32                                float
air_density_2m:kgm3            float32                                float
ceiling_height_agl:m           float32         20675      0.222429    float
clear_sky_energy_1h:J          float32                                float
clear_sky_rad:W                float32                                float
cloud_base_agl:m               float32          8547      0.091952    float
dew_or_rime:idx                float32                                float
dew_point_2m:K                 float32                                float
diffuse_rad:W                  float32                                float
diffuse_rad_1h:J               float32                                float
direct_rad:W                   float32                                float
direct_rad_1h:J                float32                                float
effective_cloud_cover:p        float32                                float
elevation:m                    float32                                float
estimated_diff_hours             int64                                  int
fresh_snow_12h:cm              float32                                float
fresh_snow_1h:cm               float32                                float
fresh_snow_24h:cm              float32                                float
fresh_snow_3h:cm               float32                                float
fresh_snow_6h:cm               float32                                float
hour                             int64                                  int
is_day:idx                     float32                                float
is_in_shadow:idx               float32                                float
is_weekend                       int64                                  int
location                        object                               object
month                            int64                                  int
msl_pressure:hPa               float32                                float
precip_5min:mm                 float32                                float
precip_type_5min:idx           float32                                float
pressure_100m:hPa              float32                                float
pressure_50m:hPa               float32                                float
prob_rime:p                    float32                                float
rain_water:kgm2                float32                                float
relative_humidity_1000hPa:p    float32                                float
sample_weight                    int64                                  int
sfc_pressure:hPa               float32                                float
```

snow_depth:cm	float32	float
snow_melt_10min:mm	float32	float
snow_water:kgm2	float32	float
sun_azimuth:d	float32	float
sun_elevation:d	float32	float
super_cooled_liquid_water:kgm2	float32	float
t_1000hPa:K	float32	float
total_cloud_cover:p	float32	float
visibility:m	float32	float
weekday	int64	int
wind_speed_10m:ms	float32	float
wind_speed_u_10m:ms	float32	float
wind_speed_v_10m:ms	float32	float
wind_speed_w_1000hPa:ms	float32	float
y	float64	float
year	int64	int

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
estimated_diff_hours	numeric	
fresh_snow_12h:cm	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_in_shadow:idx	category	
is_weekend	category	
location	category	
month	category	
msl_pressure:hPa	numeric	
precip_5min:mm	numeric	
precip_type_5min:idx	category	
pressure_100m:hPa	numeric	

pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	category
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric
year	category

test_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	2160	106			8.206482	
air_density_2m:kgm3	2160	153			1.232807	
ceiling_height_agl:m	1473	1391			2938.389648	
clear_sky_energy_1h:J	2160	1807			1227746.75	
clear_sky_rad:W	2160	1044			341.056641	
cloud_base_agl:m	1879	1771			1797.160156	
dew_or_rime:idx	2160	3			0.040741	
dew_point_2m:K	2160	202			280.783203	
diffuse_rad:W	2160	985			84.915688	
diffuse_rad_1h:J	2160	1806			305696.5	
direct_rad:W	2160	916			114.279816	
direct_rad_1h:J	2160	1634			411408.875	
effective_cloud_cover:p	2160	590			64.113792	
elevation:m	2160	3			12.333333	
estimated_diff_hours	2160	24			27.5	
fresh_snow_12h:cm	2160	2			0.000185	
fresh_snow_1h:cm	2160	2			0.000185	
fresh_snow_24h:cm	2160	2			0.000185	
fresh_snow_3h:cm	2160	2			0.000185	
fresh_snow_6h:cm	2160	2			0.000185	
hour	2160	24			11.5	
is_day:idx	2160	2			0.795833	
is_in_shadow:idx	2160	2			0.24537	

is_weekend	2160	2			0.366667
location	2160	3	A	720	
month	2160	3			5.666667
msl_pressure:hPa	2160	321			1016.805786
precip_5min:mm	2160	27			0.00775
precip_type_5min:idx	2160	3			0.065741
pressure_100m:hPa	2160	359			1002.970825
pressure_50m:hPa	2160	356			1009.007202
prob_rime:p	2160	3			0.01588
rain_water:kgm2	2160	8			0.013056
relative_humidity_1000hPa:p	2160	538			70.920792
sample_weight	2160	1			3.0
sfc_pressure:hPa	2160	363			1015.070374
snow_depth:cm	2160	1			0.0
snow_melt_10min:mm	2160	1			0.0
snow_water:kgm2	2160	16			0.060972
sun_azimuth:d	2160	1830			183.166199
sun_elevation:d	2160	1623			20.292332
super_cooled_liquid_water:kgm2	2160	7			0.065463
t_1000hPa:K	2160	254			284.737732
total_cloud_cover:p	2160	553			69.298981
visibility:m	2160	2155			33304.636719
weekday	2160	7			3.233333
wind_speed_10m:ms	2160	83			2.946759
wind_speed_u_10m:ms	2160	123			1.650694
wind_speed_v_10m:ms	2160	80			-0.187176
wind_speed_w_1000hPa:ms	2160	2			0.000324
year	2160	1			2023.0

	std	min	25%	\
absolute_humidity_2m:gm3	2.201396	3.2	6.6	
air_density_2m:kgm3	0.032116	1.142	1.209	
ceiling_height_agl:m	2913.641113	30.6	891.799988	
clear_sky_energy_1h:J	1104468.625	0.0	64338.124023	
clear_sky_rad:W	307.729095	0.0	13.65	
cloud_base_agl:m	2046.394409	29.799999	486.899994	
dew_or_rime:idx	0.202365	-1.0	0.0	
dew_point_2m:K	4.378817	268.0	277.899994	
diffuse_rad:W	78.422508	0.0	6.925	
diffuse_rad_1h:J	278146.25	0.0	36756.901367	
direct_rad:W	171.838226	0.0	0.0	
direct_rad_1h:J	611480.125	0.0	86.575001	
effective_cloud_cover:p	37.947498	0.0	30.700001	
elevation:m	8.261587	6.0	6.0	
estimated_diff_hours	6.923789	16.0	21.75	
fresh_snow_12h:cm	0.008607	0.0	0.0	
fresh_snow_1h:cm	0.008607	0.0	0.0	
fresh_snow_24h:cm	0.008607	0.0	0.0	

fresh_snow_3h:cm	0.008607	0.0	0.0
fresh_snow_6h:cm	0.008607	0.0	0.0
hour	6.923789	0.0	5.75
is_day:idx	0.403185	0.0	1.0
is_in_shadow:idx	0.430406	0.0	0.0
is_weekend	0.482006	0.0	0.0
location			
month	0.596423	5.0	5.0
msl_pressure:hPa	9.728754	986.099976	1011.5
precip_5min:mm	0.033776	0.0	0.0
precip_type_5min:idx	0.249747	0.0	0.0
pressure_100m:hPa	9.644145	971.799988	997.799988
pressure_50m:hPa	9.74076	977.700012	1003.799988
prob_rime:p	0.551282	0.0	0.0
rain_water:kgm2	0.055256	0.0	0.0
relative_humidity_1000hPa:p	15.725973	23.9	60.275
sample_weight	0.0	3.0	3.0
sfc_pressure:hPa	9.840412	983.5	1009.799988
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	-0.0	-0.0
snow_water:kgm2	0.219562	0.0	0.0
sun_azimuth:d	109.193207	8.27	85.359253
sun_elevation:d	18.681047	-11.617	1.96475
super_cooled_liquid_water:kgm2	0.115824	0.0	0.0
t_1000hPa:K	5.839595	273.700012	279.799988
total_cloud_cover:p	38.41222	0.0	32.799999
visibility:m	15624.633789	874.400024	19635.100098
weekday	2.186573	0.0	1.0
wind_speed_10m:ms	1.733865	0.0	1.5
wind_speed_u_10m:ms	2.578466	-4.3	-0.2
wind_speed_v_10m:ms	1.50826	-4.4	-1.3
wind_speed_w_1000hPa:ms	0.005685	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max \
absolute_humidity_2m:gm3	8.0	10.0	14.2
air_density_2m:kgm3	1.238	1.26	1.301
ceiling_height_agl:m	1553.900024	4021.300049	11468.0
clear_sky_energy_1h:J	1056303.125	2372037.5	3005707.0
clear_sky_rad:W	273.849991	646.874985	835.099976
cloud_base_agl:m	997.799988	2298.300049	11467.799805
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	281.0	284.299988	290.200012
diffuse_rad:W	73.700001	135.600006	312.600006
diffuse_rad_1h:J	272526.046875	488256.03125	1086246.25
direct_rad:W	16.200001	180.399994	668.0
direct_rad_1h:J	60416.199219	686746.859375	2403444.25
effective_cloud_cover:p	77.75	100.0	100.0

elevation:m	7.0	24.0	24.0
estimated_diff_hours	27.5	33.25	39.0
fresh_snow_12h:cm	0.0	0.0	0.4
fresh_snow_1h:cm	0.0	0.0	0.4
fresh_snow_24h:cm	0.0	0.0	0.4
fresh_snow_3h:cm	0.0	0.0	0.4
fresh_snow_6h:cm	0.0	0.0	0.4
hour	11.5	17.25	23.0
is_day:idx	1.0	1.0	1.0
is_in_shadow:idx	0.0	0.0	1.0
is_weekend	0.0	1.0	1.0
location			
month	6.0	6.0	7.0
msl_pressure:hPa	1020.599976	1023.799988	1029.599976
precip_5min:mm	0.0	0.0	0.34
precip_type_5min:idx	0.0	0.0	2.0
pressure_100m:hPa	1006.25	1010.099976	1016.400024
pressure_50m:hPa	1012.299988	1016.200012	1022.5
prob_rime:p	0.0	0.0	23.0
rain_water:kgm2	0.0	0.0	0.7
relative_humidity_1000hPa:p	73.900002	83.699997	98.900002
sample_weight	3.0	3.0	3.0
sfc_pressure:hPa	1018.299988	1022.299988	1028.699951
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	0.0	0.0
snow_water:kgm2	0.0	0.0	3.4
sun_azimuth:d	184.236	279.576248	356.984009
sun_elevation:d	18.54	38.102499	49.902
super_cooled_liquid_water:kgm2	0.0	0.1	0.6
t_1000hPa:K	284.799988	288.299988	302.200012
total_cloud_cover:p	95.300003	100.0	100.0
visibility:m	37623.050781	45378.099609	63863.800781
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.0	8.8
wind_speed_u_10m:ms	1.6	3.525	8.8
wind_speed_v_10m:ms	-0.3	0.8	4.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
year	2023.0	2023.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type	\
absolute_humidity_2m:gm3	float32			float	
air_density_2m:kgm3	float32			float	
ceiling_height_agl:m	float32	687	0.318056	float	
clear_sky_energy_1h:J	float32			float	
clear_sky_rad:W	float32			float	
cloud_base_agl:m	float32	281	0.130093	float	
dew_or_rime:idx	float32			float	
dew_point_2m:K	float32			float	

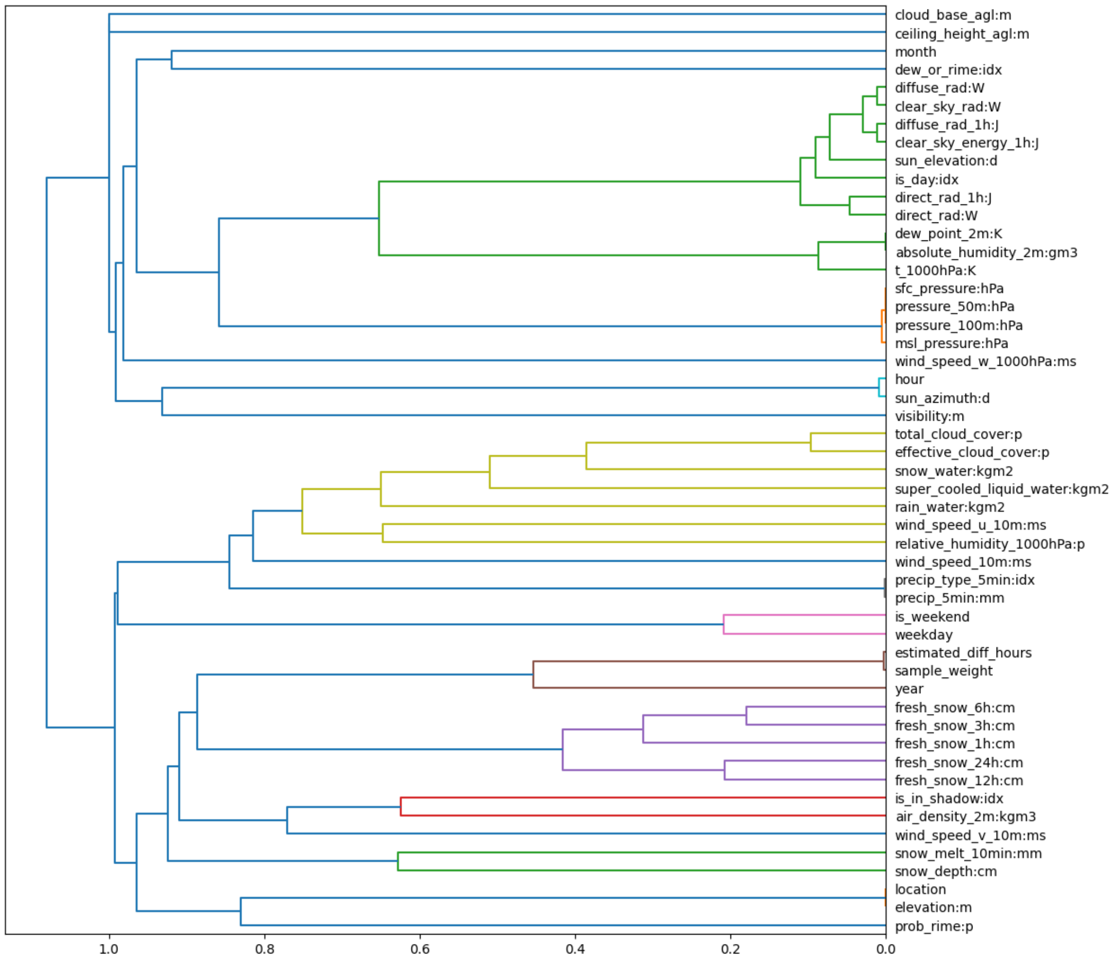
```
diffuse_rad:W                   float32                                 float
diffuse_rad_1h:J                float32                                 float
direct_rad:W                    float32                                 float
direct_rad_1h:J                 float32                                 float
effective_cloud_cover:p         float32                                 float
elevation:m                     float32                                 float
estimated_diff_hours              int64                                   int
fresh_snow_12h:cm               float32                                 float
fresh_snow_1h:cm                float32                                 float
fresh_snow_24h:cm               float32                                 float
fresh_snow_3h:cm                float32                                 float
fresh_snow_6h:cm                float32                                 float
hour                              int64                                   int
is_day:idx                      float32                                 float
is_in_shadow:idx                float32                                 float
is_weekend                        int64                                   int
location                         object                                object
month                             int64                                   int
msl_pressure:hPa                float32                                 float
precip_5min:mm                  float32                                 float
precip_type_5min:idx            float32                                 float
pressure_100m:hPa               float32                                 float
pressure_50m:hPa                float32                                 float
prob_rime:p                     float32                                 float
rain_water:kgm2                 float32                                 float
relative_humidity_1000hPa:p     float32                                 float
sample_weight                     int64                                   int
sfc_pressure:hPa                float32                                 float
snow_depth:cm                   float32                                 float
snow_melt_10min:mm              float32                                 float
snow_water:kgm2                 float32                                 float
sun_azimuth:d                   float32                                 float
sun_elevation:d                 float32                                 float
super_cooled_liquid_water:kgm2  float32                                 float
t_1000hPa:K                     float32                                 float
total_cloud_cover:p             float32                                 float
visibility:m                    float32                                 float
weekday                           int64                                   int
wind_speed_10m:ms               float32                                 float
wind_speed_u_10m:ms             float32                                 float
wind_speed_v_10m:ms             float32                                 float
wind_speed_w_1000hPa:ms         float32                                 float
year                              int64                                   int

                               variable_type special_types
absolute_humidity_2m:gm3             numeric
air_density_2m:kgm3                  numeric
ceiling_height_agl:m                 numeric
```

clear_sky_energy_1h:J	numeric
clear_sky_rad:W	numeric
cloud_base_agl:m	numeric
dew_or_rime:idx	category
dew_point_2m:K	numeric
diffuse_rad:W	numeric
diffuse_rad_1h:J	numeric
direct_rad:W	numeric
direct_rad_1h:J	numeric
effective_cloud_cover:p	numeric
elevation:m	category
estimated_diff_hours	numeric
fresh_snow_12h:cm	category
fresh_snow_1h:cm	category
fresh_snow_24h:cm	category
fresh_snow_3h:cm	category
fresh_snow_6h:cm	category
hour	numeric
is_day:idx	category
is_in_shadow:idx	category
is_weekend	category
location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	category
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	category
snow_melt_10min:mm	category
snow_water:kgm2	category
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
year	category

Types warnings summary

```
  train_data test_data warnings
y      float        --  warning
```

1.0.1 Feature Distance

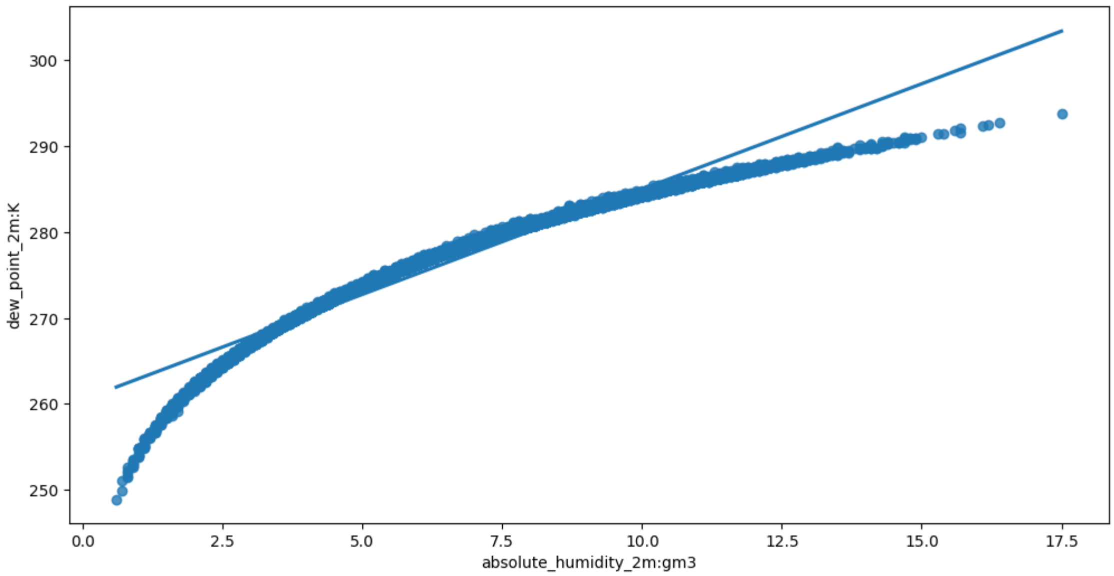


The following feature groups are considered as near-duplicates:

Distance threshold: <= `0.01`. Consider keeping only some of the columns within each group:

- `elevation:m`, `location` - distance `0.00`
- `absolute_humidity_2m:gm3`, `dew_point_2m:K` - distance `0.00`
- `precip_5min:mm`, `precip_type_5min:idx` - distance `0.00`
- `estimated_diff_hours`, `sample_weight` - distance `0.00`
- `msl_pressure:hPa`, `pressure_100m:hPa`, `pressure_50m:hPa`, `sfc_pressure:hPa` - distance `0.00`
- `hour`, `sun_azimuth:d` - distance `0.01`

Feature interaction between `absolute_humidity_2m:gm3`/`dew_point_2m:K`



Feature interaction between `msl_pressure:hPa`/`pressure_100m:hPa`

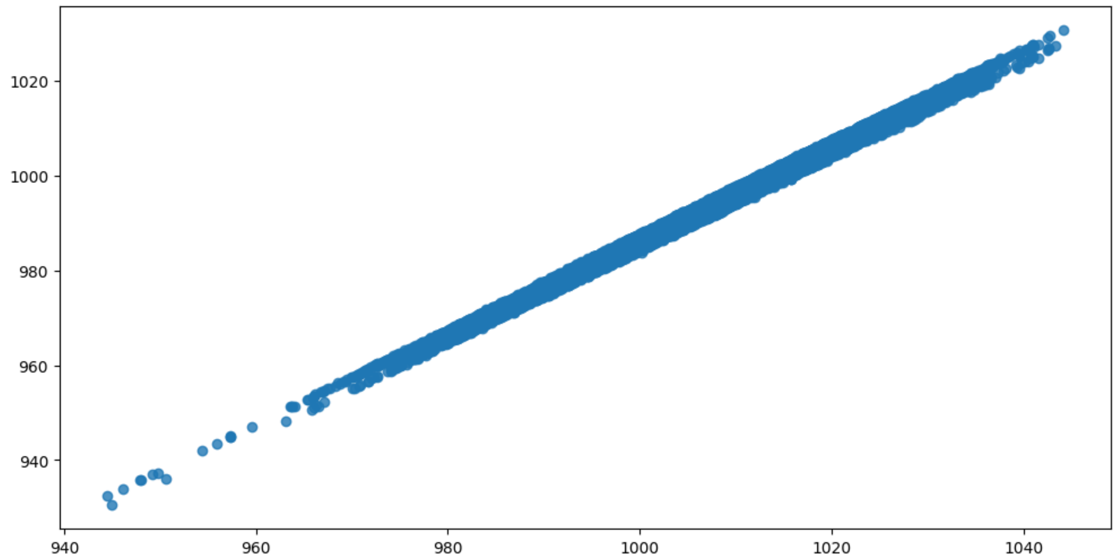
```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/data/autogluon_each_location.ipynb Cell 4
 ↪line 2
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
 ↪autogluon_each_location.ipynb#X65sZmlsZQ%3D%3D?line=0'>1</a> import autogluon
 ↪eda.auto as auto
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
 ↪autogluon_each_location.ipynb#X65sZmlsZQ%3D%3D?line=1'>2</a> auto.
 ↪dataset_overview(train_data=X_train, test_data=X_test, label="y", sample=None

File ~/.local/lib/python3.10/site-packages/autogluon/eda/auto/simple.py:639, in
 ↪dataset_overview(train_data, test_data, val_data, label, state, return_state,
 ↪sample, fig_args, chart_args)
    630                 interactions.append(MarkdownSectionComponent(f"Feature
 ↪interaction between `{nodes[0]}`/`{n}`"))
    631                 interactions.append(
    632                     FeatureInteractionVisualization(
    633                         key=f"{nodes[0]}:{n}",
   (…)
    636                     )
    637                 )
--> 639         analyze(
    640             train_data=train_data,
    641             state=state,
    642             anlz_facets=[FeatureInteraction(key=f"{nodes[0]}:{n}",
 ↪x=nodes[0], y=n) for n in nodes[1:]],
```

```
    643             viz_facets=[
    644                 *interactions,
    645             ],
    646         )
    648 return state if return_state else None

File ~/.local/lib/python3.10/site-packages/autogluon/eda/auto/simple.py:182, in
 ↪analyze(train_data, test_data, val_data, model, label, state, sample,
 ↪anlz_facets, viz_facets, return_state, verbosity, **kwargs)
    166 analysis = BaseAnalysis(
    167     state=state,
    168     train_data=train_data,
   (…)
    175     ],
    176 )
    178 state = analysis.fit()
    180 SimpleVerticalLinearLayout(
    181     facets=viz_facets,
--> 182 ).render(state)
    184 root_logger.setLevel(root_log_level)  # Reset log level
    186 return state if return_state else None

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/base.py:
 ↪96, in AbstractVisualization.render(self, state)
     94 state = self._get_namespace_state(state)
     95 if self.can_handle(state):
---> 96     self._render(state)

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/layouts.
 ↪py:43, in SimpleVerticalLinearLayout._render(self, state)
     41 def _render(self, state: AnalysisState) -> None:
     42     for facet in self.facets:
---> 43         facet.render(state)

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/base.py:
 ↪96, in AbstractVisualization.render(self, state)
     94 state = self._get_namespace_state(state)
     95 if self.can_handle(state):
---> 96     self._render(state)

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/
 ↪interaction.py:306, in FeatureInteractionVisualization._render(self, state)
    303 if "figsize" not in fig_args:
    304     fig_args["figsize"] = (12, 6)
--> 306 renderer.render(
    307     state=state,
    308     ds=ds,
    309     params=(x, y, hue),
```

```
    310     param_types=(x_type, y_type, hue_type),
    311     data=data,
    312     fig_args=fig_args,
    313     chart_args=chart_args,
    314 )

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/interaction.py:116, in _AbstractFeatureInteractionPlotRenderer.render(self, state, ds, params, param_types, data, fig_args, chart_args)
    114 def render(self, state, ds, params, param_types, data, fig_args, chart_args):
    115     fig, ax = plt.subplots(**fig_args)
--> 116     self._render(state, ds, params, param_types, ax, data, chart_args)
    117     plt.show(fig)

File ~/.local/lib/python3.10/site-packages/autogluon/eda/visualization/interaction.py:454, in FeatureInteractionVisualization._RegPlotRenderer._render(self, state, ds, params, param_types, ax, data, chart_args)
    453 def _render(self, state, ds, params, param_types, ax, data, chart_args)
--> 454     sns.regplot(ax=ax, data=data, **chart_args)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:759, in regplot(data, x, y, x_estimator, x_bins, x_ci, scatter, fit_reg, ci, n_boot, units, seed, order, logistic, lowess, robust, logx, x_partial, y_partial, truncate, dropna, x_jitter, y_jitter, label, color, marker, scatter_kws, line_kws, ax)
    757 scatter_kws["marker"] = marker
    758 line_kws = {} if line_kws is None else copy.copy(line_kws)
--> 759 plotter.plot(ax, scatter_kws, line_kws)
    760 return ax

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:368, in _RegressionPlotter.plot(self, ax, scatter_kws, line_kws
    365     self.scatterplot(ax, scatter_kws)
    367 if self.fit_reg:
--> 368     self.lineplot(ax, line_kws)
    370 # Label the axes
    371 if hasattr(self.x, "name"):

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:413, in _RegressionPlotter.lineplot(self, ax, kws)
    411 """Draw the model."""
    412 # Fit the regression model
--> 413 grid, yhat, err_bands = self.fit_regression(ax)
    414 edges = grid[0], grid[-1]
    416 # Get set default aesthetics
```

```
File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:219, in _RegressionPlotter.fit_regression(self, ax, x_range, grid)
    217     yhat, yhat_boots = self.fit_logx(grid)
    218 else:
--> 219     yhat, yhat_boots = self.fit_fast(grid)
    221 # Compute the confidence interval at each grid point
    222 if ci is None:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:240, in _RegressionPlotter.fit_fast(self, grid)
    237 if self.ci is None:
    238     return yhat, None
--> 240 beta_boots = algo.bootstrap(X, y,
    241                             func=reg_func,
    242                             n_boot=self.n_boot,
    243                             units=self.units,
    244                             seed=self.seed).T
    245 yhat_boots = grid.dot(beta_boots).T
    246 return yhat, yhat_boots

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/algorithms.py:98, in bootstrap(*args, **kwargs)
     96     resampler = integers(0, n, n, dtype=np.intp)  # intp is indexing dtype
     97     sample = [a.take(resampler, axis=0) for a in args]
---> 98     boot_dist.append(f(*sample, **func_kwargs))
     99 return np.array(boot_dist)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/seaborn/regression.py:232, in _RegressionPlotter.fit_fast.<locals>.reg_func(_x, _y)
    231 def reg_func(_x, _y):
--> 232     return np.linalg.pinv(_x).dot(_y)

File <__array_function__ internals>:200, in pinv(*args, **kwargs)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/numpy/linalg/linalg.py:1983, in pinv(a, rcond, hermitian)
   1981     return wrap(res)
   1982 a = a.conjugate()
-> 1983 u, s, vt = svd(a, full_matrices=False, hermitian=hermitian)
   1985 # discard small singular values
   1986 cutoff = rcond[..., newaxis] * amax(s, axis=-1, keepdims=True)

File <__array_function__ internals>:200, in svd(*args, **kwargs)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/numpy/linalg/linalg.py:1642, in svd(a, full_matrices, compute_uv, hermitian)
```

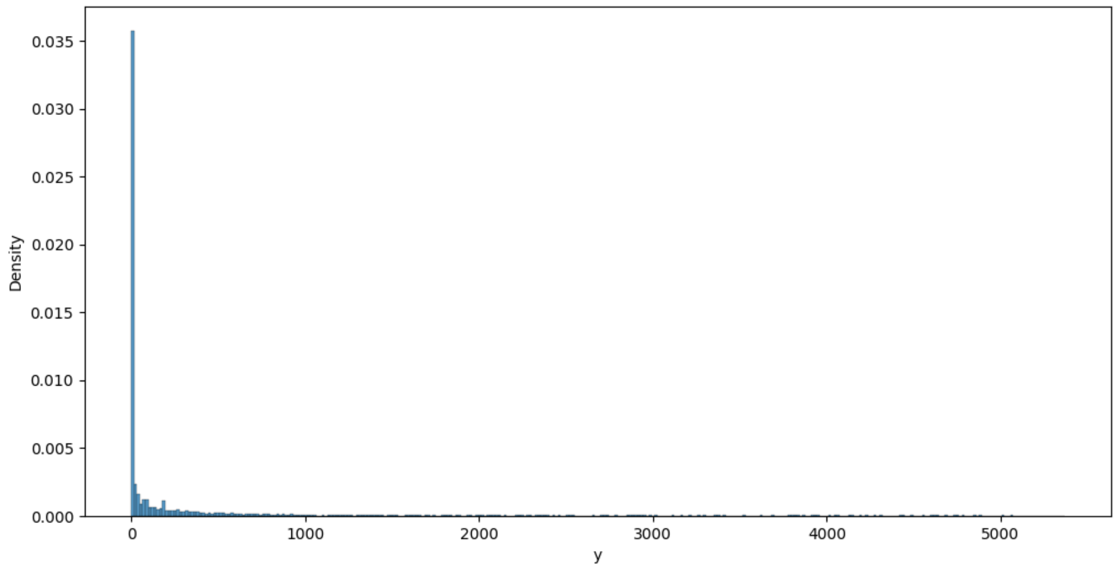
```
   1639         gufunc = _umath_linalg.svd_n_s
   1641 signature = 'D->DdD' if isComplexType(t) else 'd->ddd'
-> 1642 u, s, vh = gufunc(a, signature=signature, extobj=extobj)
   1643 u = u.astype(result_t, copy=False)
   1644 s = s.astype(_realType(result_t), copy=False)

KeyboardInterrupt:
```




```
[ ]: auto.target_analysis(train_data=X_train, label="y")
```

1.1 Target variable analysis

```
   count       mean        std  min   25%   50%    75%      max   dtypes  \
y  10000  295.26029  787.46272 -0.0   0.0   0.0  176.4  5365.36  float64

   unique missing_count missing_ratio raw_type special_types
y    2539                                 float
```

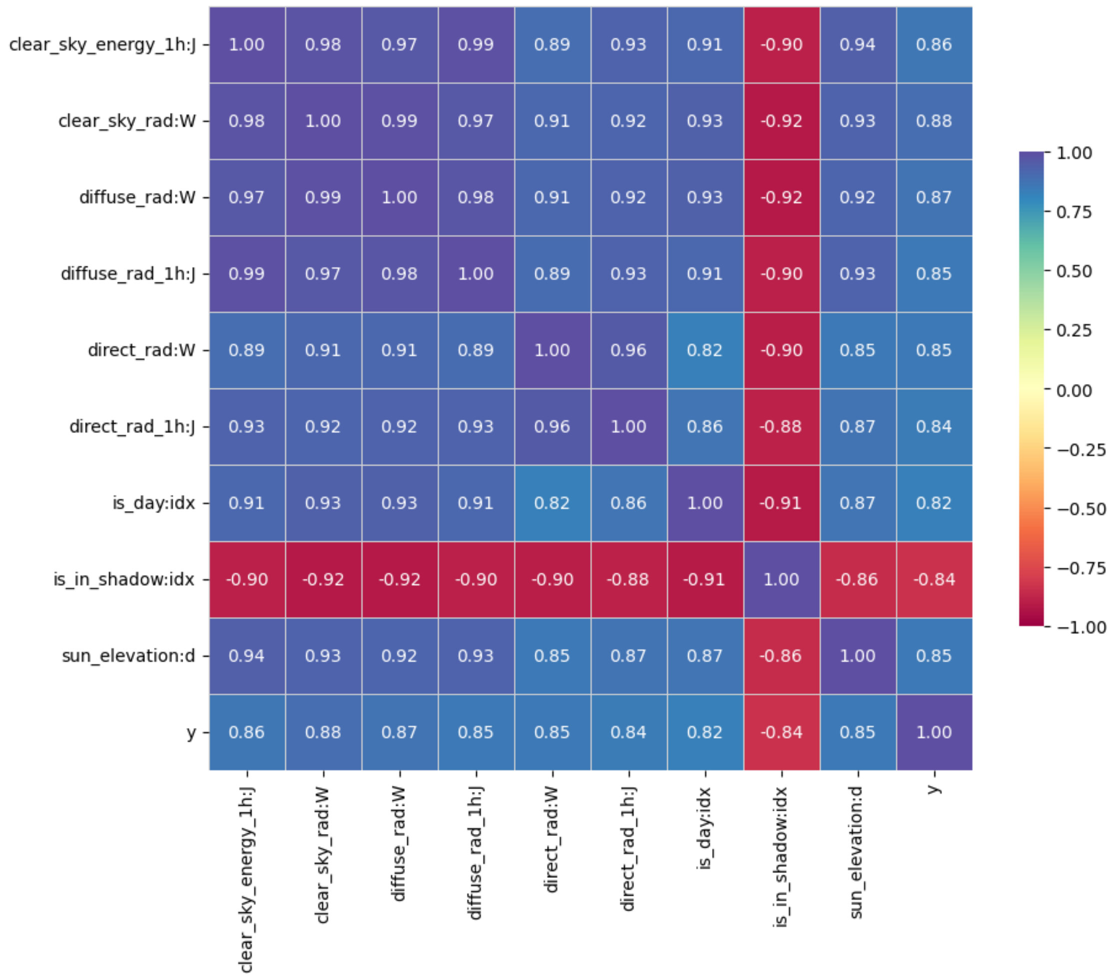


1.1.1 Distribution fits for target variable

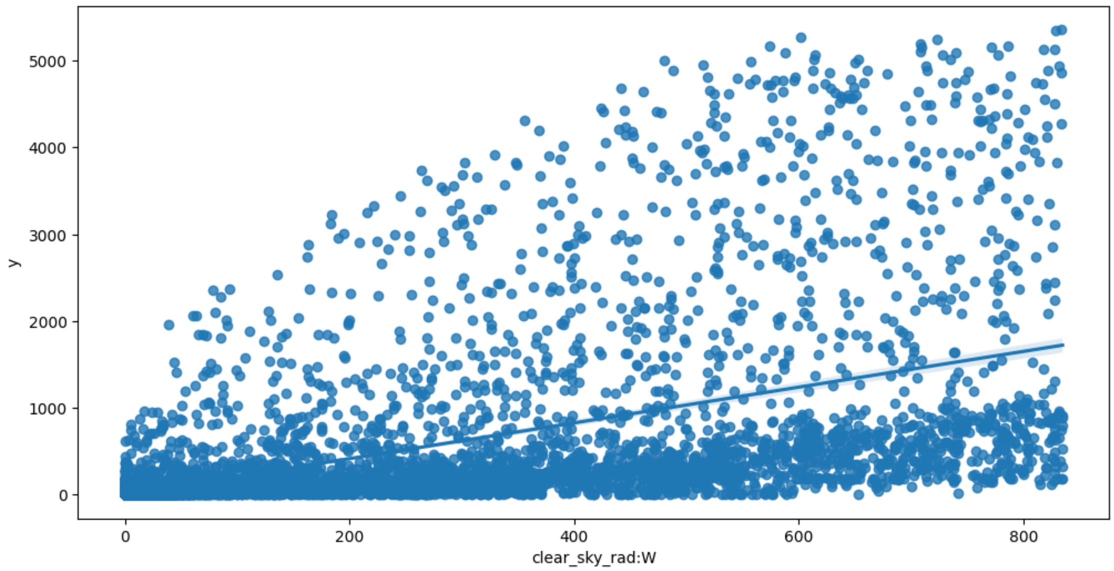
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

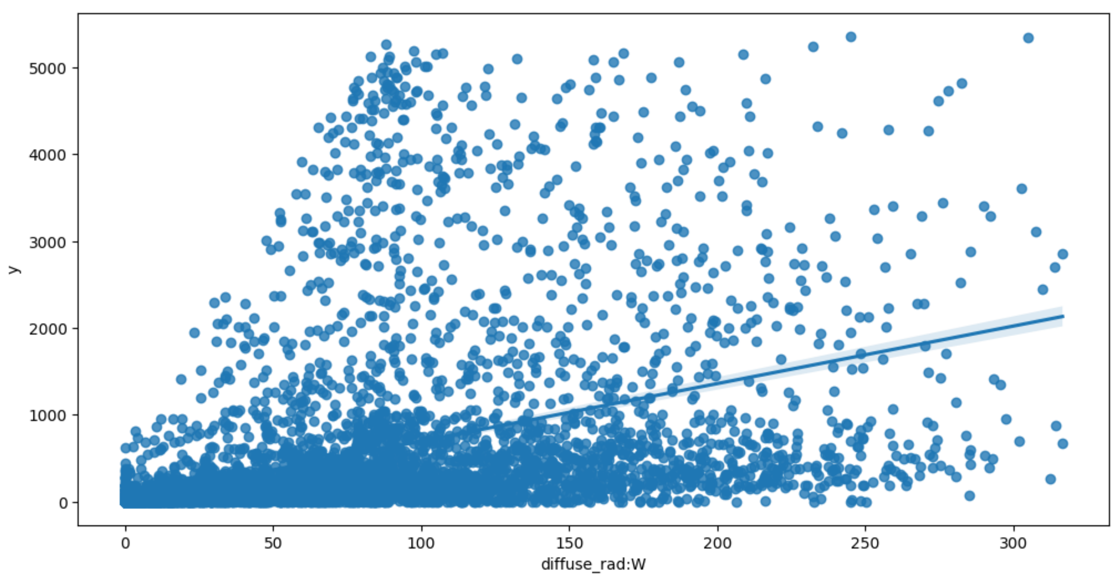
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



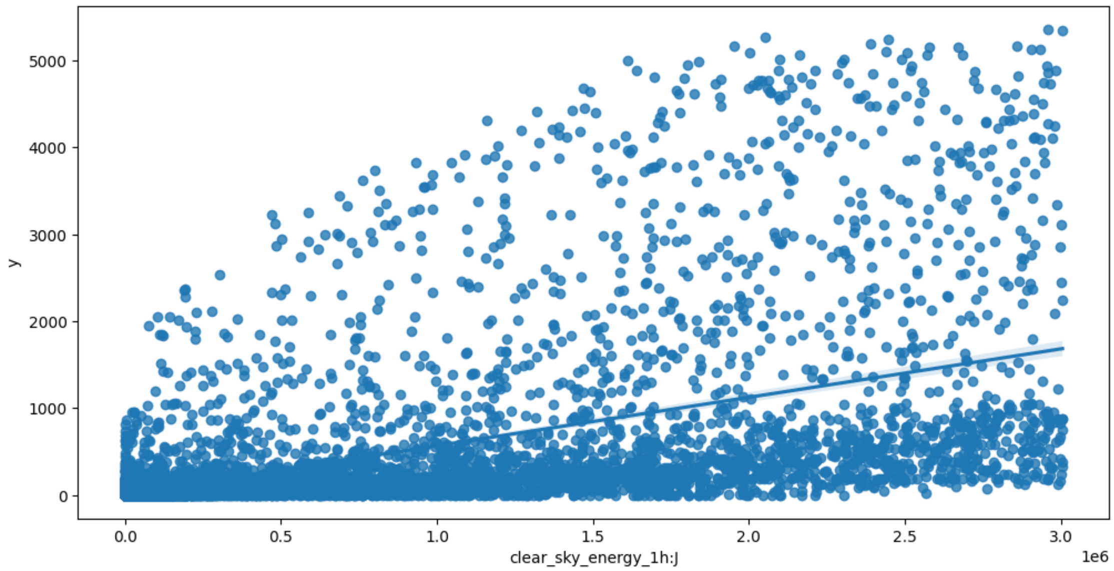
Feature interaction between `clear_sky_rad:W/y` in `train_data` (sample size: 10000)



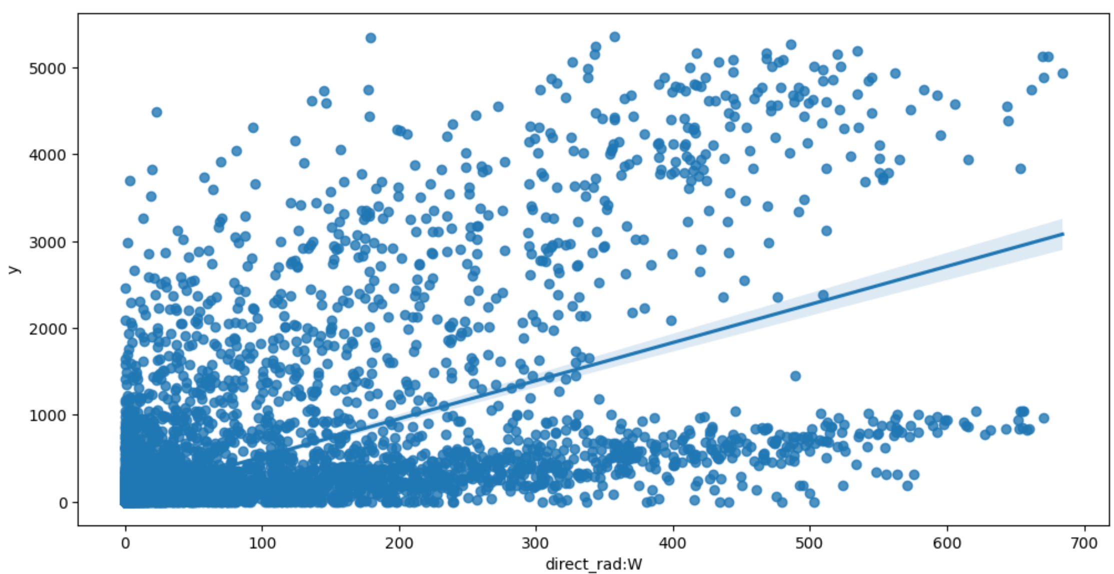
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



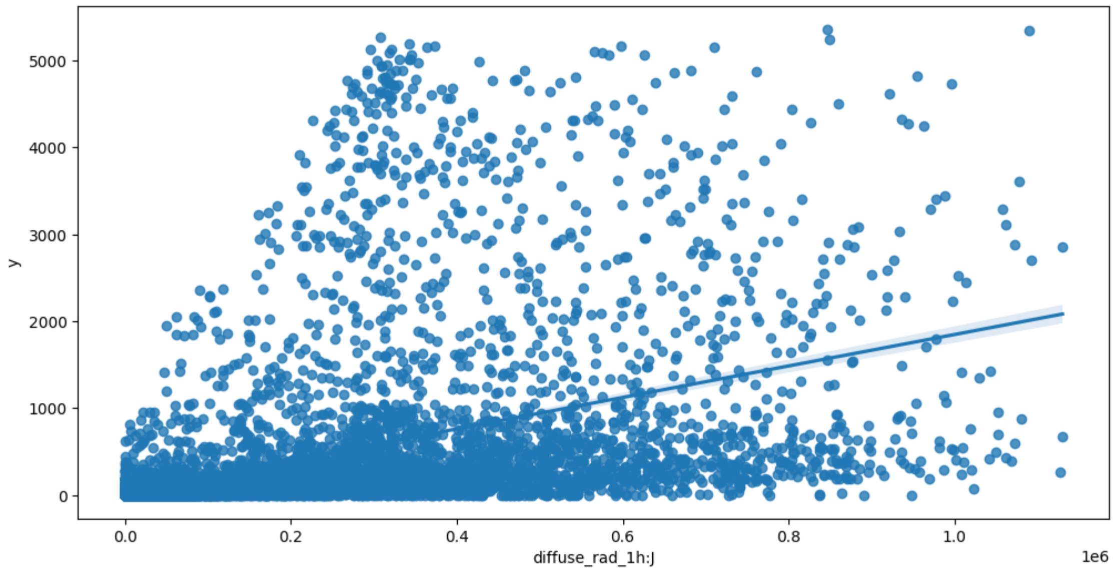
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



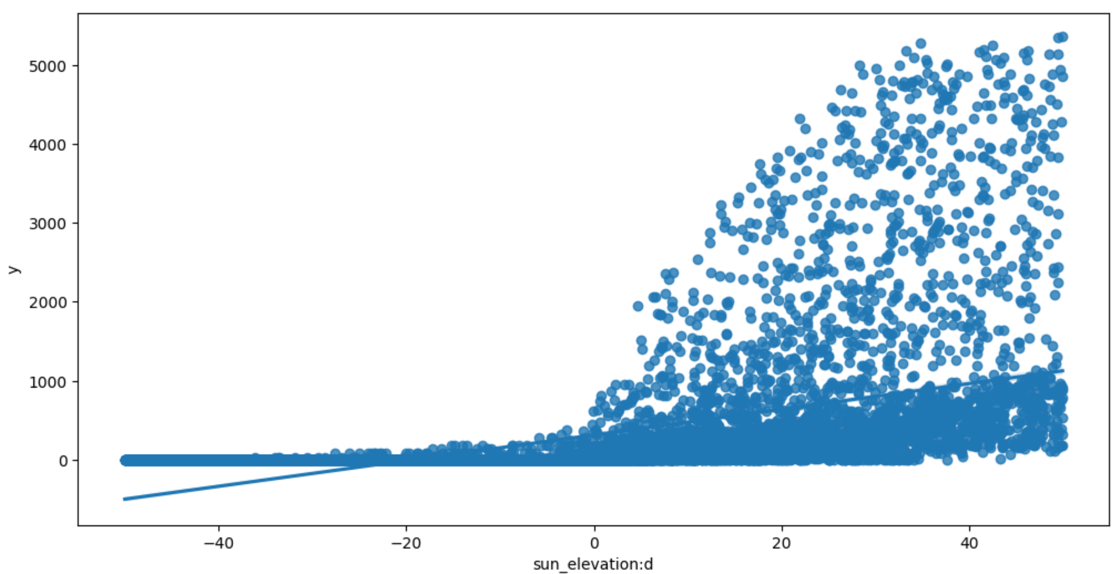
Feature interaction between `direct_rad:W`/`y` in `train_data` (sample size: 10000)



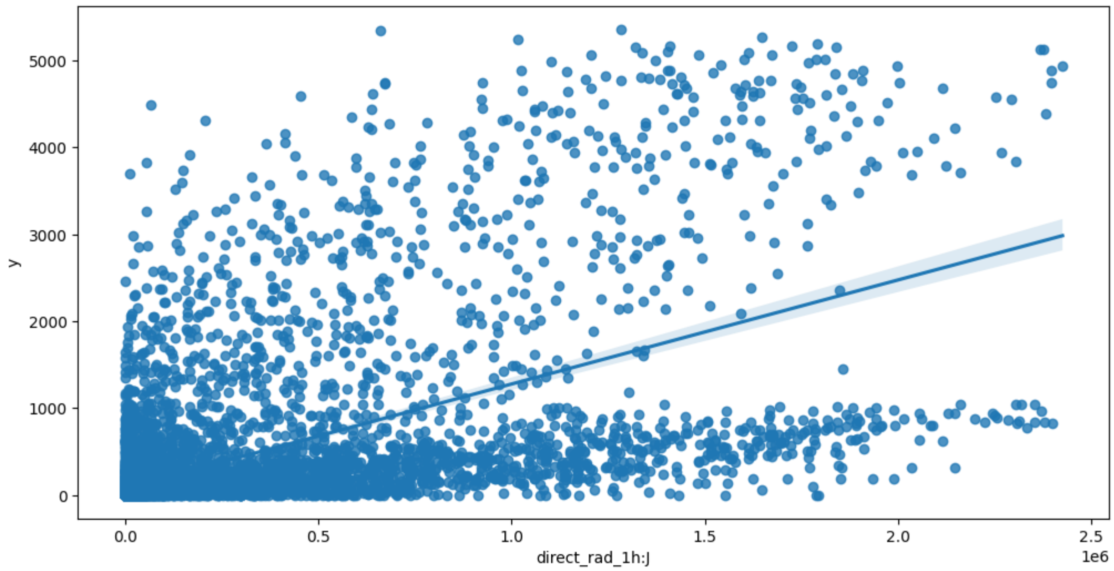
Feature interaction between `diffuse_rad_1h:J`/`y` in `train_data` (sample size: 10000)



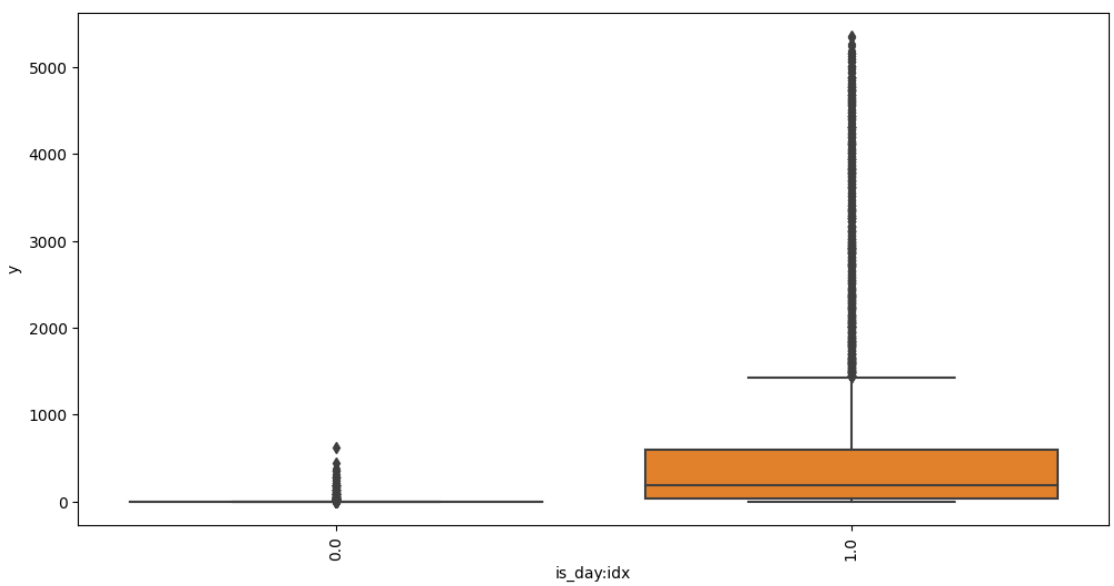
Feature interaction between `sun_elevation:d/y` in `train_data` (sample size: 10000)



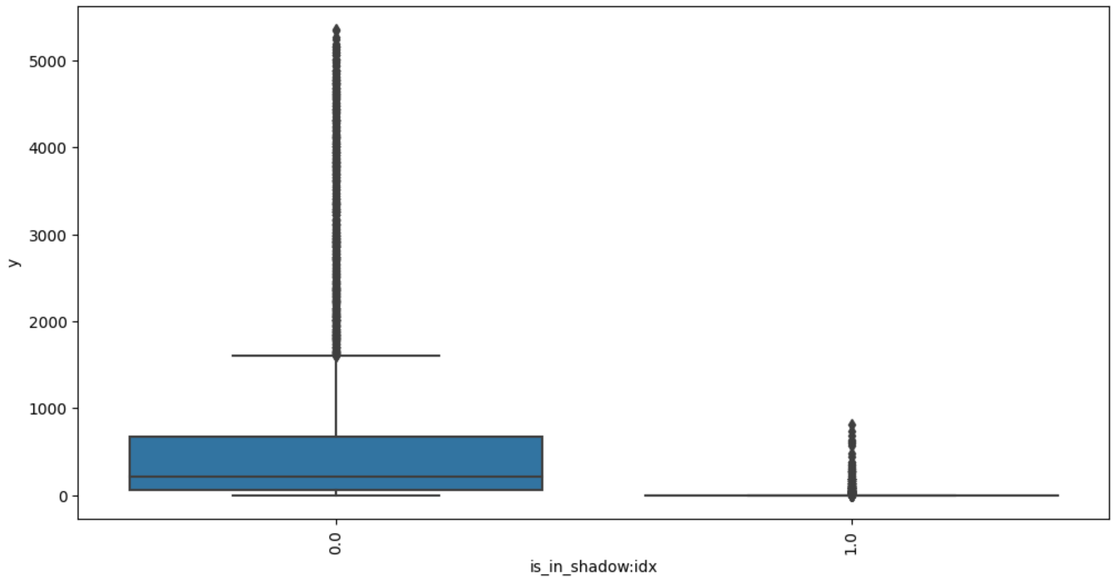
Feature interaction between `direct_rad_1h:J/y` in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx/y` in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx/y` in `train_data` (sample size: 10000)



2 Starting

[ ]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 78
Now creating submission number: 79
New filename: submission_79_jorge
```

[ ]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)
```

```
label = 'y'
metric = 'mean_absolute_error'
time_limit = 60
presets = 'best_quality'

sample_weight = 'sample_weight' #None
weight_evaluation = True #False
```

```
Loaded data from: X_train_raw.csv | Columns = 53 / 53 | Rows = 93024 -> 93024
```

[ ]:
```
predictors = [None, None, None]
```

[ ]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
↪== loc], time_limit=time_limit, presets=presets)
predictors[0] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_jorge_A"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
```

```
Training model for location A…
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/data/autogluon_each_location.ipynb Cell 1␣
↪line 3
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#Y104sZmlsZQ%3D%3D?line=0'>1</a> loc = "A"
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#Y104sZmlsZQ%3D%3D?line=1'>2</a> print(f"Trainin␣
↪model for location {loc}…")
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#Y104sZmlsZQ%3D%3D?line=2'>3</a> predictor =␣
↪TabularPredictor(label=label, eval_metric=metric, path=f"AutogluonModels/
↪{new_filename}_{loc}", sample_weight=sample_weight,␣
↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"] ==␣
↪loc], time_limit=time_limit, presets=presets)
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#Y104sZmlsZQ%3D%3D?line=3'>4</a> predictors[0] =␣
↪predictor

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪utils/decorators.py:31, in unpack.<locals>._unpack_inner.<locals>._call(*args␣
↪**kwargs)
```

```
     28 @functools.wraps(f)
     29 def _call(*args, **kwargs):
     30     gargs, gkwargs = g(*other_args, *args, **kwargs)
---> 31     return f(*gargs, **gkwargs)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/predictor/predictor.py:986, in TabularPredictor.fit(self, train_data,
↪tuning_data, time_limit, presets, hyperparameters, feature_metadata,
↪infer_limit, infer_limit_batch_size, fit_weighted_ensemble,
↪calibrate_decision_threshold, num_cpus, num_gpus, **kwargs)
    984     aux_kwargs["fit_weighted_ensemble"] = False
    985 self.save(silent=True)  # Save predictor to disk to enable prediction
↪and training after interrupt
--> 986 self._learner.fit(
    987     X=train_data,
    988     X_val=tuning_data,
    989     X_unlabeled=unlabeled_data,
    990     holdout_frac=holdout_frac,
    991     num_bag_folds=num_bag_folds,
    992     num_bag_sets=num_bag_sets,
    993     num_stack_levels=num_stack_levels,
    994     hyperparameters=hyperparameters,
    995     core_kwargs=core_kwargs,
    996     aux_kwargs=aux_kwargs,
    997     time_limit=time_limit,
    998     infer_limit=infer_limit,
    999     infer_limit_batch_size=infer_limit_batch_size,
   1000     verbosity=verbosity,
   1001     use_bag_holdout=use_bag_holdout,
   1002 )
   1003 self._set_post_fit_vars()
   1005 self._post_fit(
   1006     keep_only_best=kwargs["keep_only_best"],
   1007     refit_full=kwargs["refit_full"],
   (…)
   1012     infer_limit=infer_limit,
   1013 )

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/learner/abstract_learner.py:158, in AbstractTabularLearner.fit(self,
↪X, X_val, **kwargs)
    156 if self.is_fit:
    157     raise AssertionError("Learner is already fit.")
--> 158 self._validate_fit_input(X=X, X_val=X_val, **kwargs)
    159 return self._fit(X=X, X_val=X_val, **kwargs)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/learner/abstract_learner.py:376, in AbstractTabularLearner.
↪_validate_fit_input(self, X, **kwargs)
```

```
    374     raise KeyError(f"Label column '{self.label}' is missing from␣
  ↪training data. Training data columns: {list(X.columns)}")
    375 X_val = kwargs.get("X_val", None)
--> 376 self._validate_sample_weight(X, X_val)
    377 self._validate_groups(X, X_val)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
  ↪tabular/learner/abstract_learner.py:390, in AbstractTabularLearner.
  ↪_validate_sample_weight(self, X, X_val)
    388 weight_vals = X[self.sample_weight]
    389 if weight_vals.isna().sum() > 0:
--> 390     raise ValueError(f"Sample weights in column '{self.sample_weight}'␣
  ↪cannot be nan")
    391 if weight_vals.dtype.kind not in "biuf":
    392     raise ValueError(f"Sample weights in column '{self.sample_weight}'␣
  ↪must be numeric values")

ValueError: Sample weights in column 'sample_weight' cannot be nan
```

[ ]:
```
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
  ↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
  ↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
  ↪== loc], time_limit=time_limit, presets=presets)
predictors[1] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_81_jorge_B/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   29.45 GB / 494.38 GB (6.0%)
Train Data Rows:    32844
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.82478, 193.94649)
        If 'regression' is not the correct problem_type, please manually specify
```

```
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4331.9 MB
        Train Data (Original)  Memory Usage: 14.52 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.38 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.12s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
```

```
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.91s of the
59.88s of remaining time.

Training model for location B…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 195.85s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 36.88s of the
56.85s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 220.95s compared to 47.91s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 33.46s of the
53.43s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -25.7449         = Validation score   (-mean_absolute_error)
        28.32s   = Training   runtime
        65.73s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.88s of the
14.16s of remaining time.
        -25.7449         = Validation score   (-mean_absolute_error)
        0.01s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
```

```
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 14.1s of the
14.06s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -24.2516         = Validation score   (-mean_absolute_error)
        5.29s    = Training   runtime
        1.3s     = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 4.97s of the 4.94s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -23.6458         = Validation score   (-mean_absolute_error)
        1.99s    = Training   runtime
        0.19s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 0.91s of the
0.89s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        25.62s   = Training   runtime
        0.85s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.88s of the
-25.95s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        0.14s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 86.12s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_81_jorge_B/")
```

[ ]:
```python
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}", sample_weight=sample_weight,␣
 ↪weight_evaluation=weight_evaluation).fit(train_data[train_data["location"]␣
 ↪== loc], time_limit=time_limit, presets=presets)
predictors[2] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_81_jorge_C/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
```

```
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   28.83 GB / 494.38 GB (5.8%)
Train Data Rows:    26095
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 77.63106, 165.81688)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4428.79 MB
        Train Data (Original)  Memory Usage: 11.53 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
```

```
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 9.84 MB (0.2% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.9s of the
59.87s of remaining time.

Training model for location C…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 99.89s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.94s of the
57.9s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 86.14s compared to 49.3s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.25s of the
56.21s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -17.0996         = Validation score   (-mean_absolute_error)
        23.53s   = Training   runtime
        44.64s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 4.44s of the 24.41s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -19.0788         = Validation score   (-mean_absolute_error)
        4.37s    = Training   runtime
        1.22s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.87s of the
17.79s of remaining time.
        -17.0784         = Validation score   (-mean_absolute_error)
        0.09s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 17.69s of the
17.68s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.7999         = Validation score   (-mean_absolute_error)
        2.08s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 13.48s of the 13.48s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -17.2792         = Validation score   (-mean_absolute_error)
        1.61s    = Training   runtime
        0.12s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 10.02s of the
10.01s of remaining time.
        -17.0599         = Validation score   (-mean_absolute_error)
        19.24s   = Training   runtime
        0.52s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.87s of the
-9.96s of remaining time.
        -16.9596         = Validation score   (-mean_absolute_error)
        0.14s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 70.12s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_81_jorge_C/")
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 51 / 51 | Rows = 93024 -> 93024
Loaded data from: X_test_raw.csv | Columns = 50 / 50 | Rows = 2160 -> 2160
```

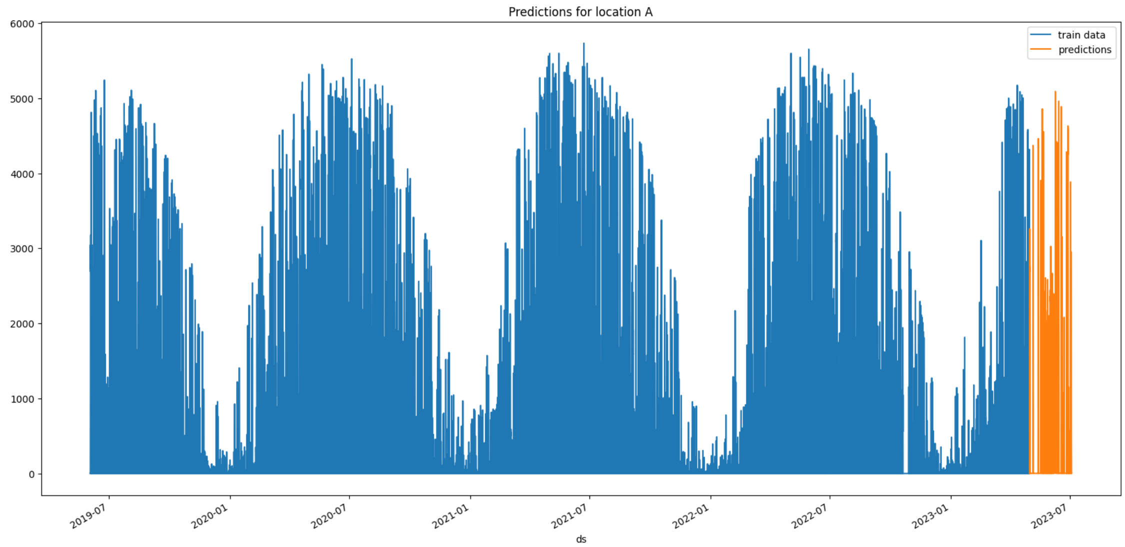
[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",
 ↪"location"], left_on=["ds", "location"])

#test_data_merged
```

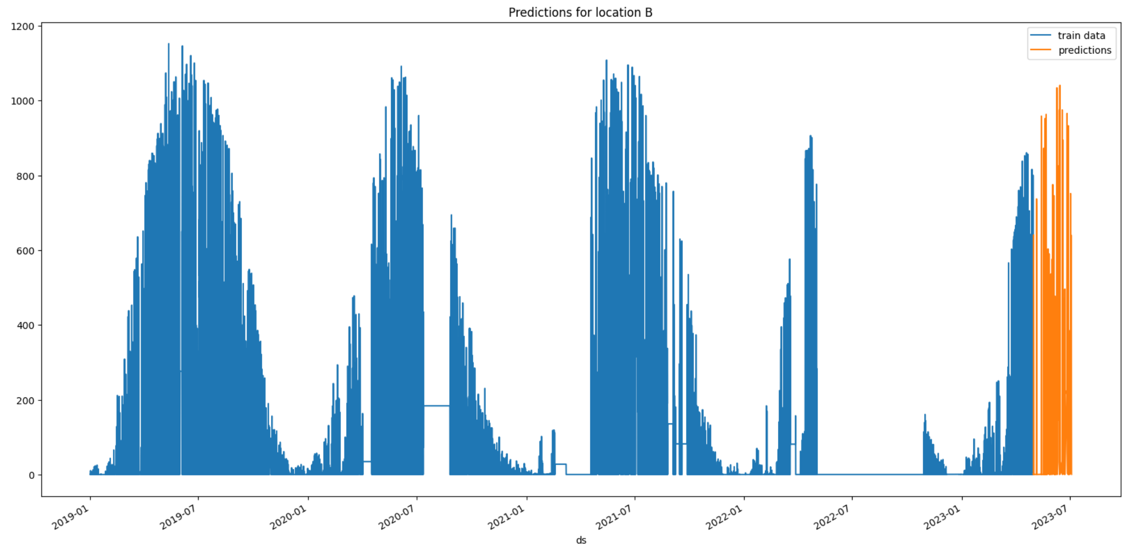
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

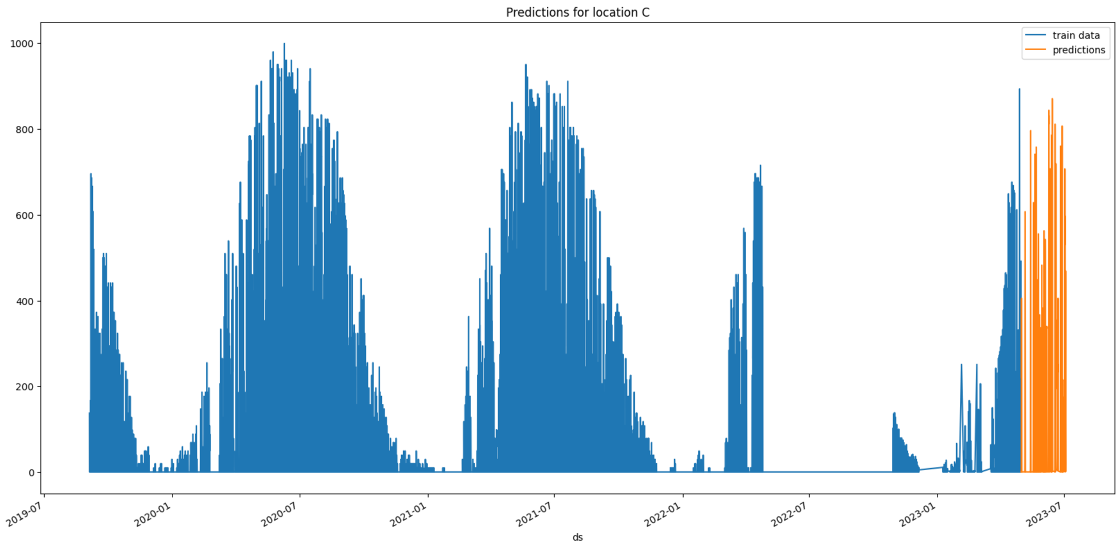
[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',
 ↪y='y', ax=ax, label="train data")
```

```python
    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```







[ ]:
```python
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
        id  prediction
0        0    1.474567
1        1    1.537354
2        2    1.680374
3        3   47.797668
4        4  300.030823
..     ...         ...
715   2155   83.732719
716   2156   61.742329
717   2157   29.696980
718   2158    3.763743
719   2159    2.140930

[2160 rows x 2 columns]
```

[ ]:
```python
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
```

```
Saving submission to submissions/submission_81_jorge.csv
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_81_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_81_jorge_files/notebook_pdfs
[NbConvertApp] Writing 121410 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 372019 bytes to notebook_pdfs/submission_81_jorge.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_81_jorge.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```

[ ]:
```
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
↪time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['location']
Computing feature importance via permutation shuffling for 48 features using
1440 rows with 5 shuffle sets…
        639.68s = Expected runtime (127.94s per shuffle set)
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictor.feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

[ ]:
```
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/Users/skog/Documents/1-2023-autumn/school/TDT4173-machine-learning/project/
↪TDT4173/autogluon_each_location.ipynb Cell 22 line 1
----> <a href='vscode-notebook-cell:/Users/skog/Documents/1-2023-autumn/school/
↪TDT4173-machine-learning/project/TDT4173/autogluon_each_location.
↪ipynb#X30sZmlsZQ%3D%3D?line=0'>1</a> subprocess.run(["jupyter", "nbconvert",␣
↪"--to", "pdf", "--output", os.path.join('notebook_pdfs',␣
↪f"{new_filename}_with_feature_importance.pdf"), "autogluon_each_location.
↪ipynb"])

NameError: name 'subprocess' is not defined
```

[ ]:

```python
import subprocess

def execute_git_command(directory, command):
    """Execute a Git command in the specified directory."""
    try:
        result = subprocess.check_output(['git', '-C', directory] + command,␣
 ↪stderr=subprocess.STDOUT)
        return result.decode('utf-8').strip(), True
    except subprocess.CalledProcessError as e:
        print(f"Git command failed with message: {e.output.decode('utf-8').
 ↪strip()}")
        return e.output.decode('utf-8').strip(), False

git_repo_path = "."

new_filename = "henrik"

branch_name = new_filename

# add datetime to branch name
branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

commit_msg = "run result"

execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# Navigate to your repo and commit changes
execute_git_command(git_repo_path, ['add', '.'])
execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# Push to remote
output, success = execute_git_command(git_repo_path, ['push',␣
 ↪'origin',branch_name])
```

```
# If the push fails, try setting an upstream branch and push again
if not success and 'upstream' in output:
    print("Attempting to set upstream and push again...")
    execute_git_command(git_repo_path, ['push', '--set-upstream',␣
 ↪'origin',branch_name])
    execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

execute_git_command(git_repo_path, ['checkout', 'main'])
```